QATAR UNIVERSITY

COLLEGE OF ENGINEERING

ECO-EFFICIENCY ASSESSMENT OF ELECTRIC VEHICLES IN THE EUROPEAN UNION COUNTRIES: THE CASE OF MIX-SOURCES OF ENERGY

BY

MUNERA HAMAD BUTTI AL-NUAIMI

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COMMITTEE PAGE

The members of the Committee approve the Thesis of

Munera Hamad Butti Al-Nuaimi defended on 12/05/2020.

Galal M Mohammed Abdella

Thesis Supervisor

Nuri Onat

Thesis Co-Supervisor

Khaled Salah Shaaban

Committee Member

Pilsung Choe

Committee Member

Murat Kucukvar

Committee Member

Gurkan Kumbaroglu

Committee Member

Approved:

Khalid AL Naji, Dean, College of Engineering

ABSTRACT

Al-Nuaimi Munera H, Master Degree: June: 2020, Master of Science in Engineering Management

Title: Eco-Efficiency Assessment Of Electric Vehicles In The European Union Countries: The Case Of Mix-Sources Of Energy

Supervisor: Dr. Galal M Abdella.

European Union (EU) member states have considered the environmental impacts of transportation and have prompted Electric Vehicle (EV) usage as one of the technological advancements that could reduce emissions and energy and water consumption. However, this depends on how EVs react to eco-friendly behaviors during their life cycle. The research utilizes a combined life cycle assessment (LCA) and a principal component analysis (PCA) technique to assess the eco-efficiency performance of EVs in EU member states. Considering the energy mix for electricity generation, three environmental indicators (GHG emission, water consumption, and energy consumption) and one economical (contribution to GDP) indicator were used to compute the eco-efficiency scores for 28 EU member states. First, the values for each environmental and economic indicators were obtained. The eco-efficiency scores for each corresponding EU member states were then calculated and compared. From the results of the eco-efficiency analysis, Belgium was found to have the highest eco-efficiency score, while Estonia was tagged to be the least eco-efficient country.

DEDICATION

This work is dedicated to My Family and Respected Qatar University instructors.

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CHAPTER 1: INTRODUCTION

This chapter will introduce an overview of the electric vehicles impacts on the environment. It will start with the effects of transportation, and then it will list different factors that influence electric vehicle adoption. Also, this chapter will shed light on the experience of EU countries when adopting electric vehicles. Finally, the thesis aims and objectives will be stated.

1.1 Overview

Unsustainable growth patterns have brunt several developing nations around the globe with increased environmental footprints, advocating the integration of sustainable development with the existing growth pattern (Bennbea et al., 2018). When analyzing various sectors from a global perspective, the transportation sector has tremendous strains on the environment, besides the construction and manufacturing sector. Prolonged effects of global climate changes, energy security, greenhouse gas (GHG) emissions and, quality of air are among the few environmental distortions that the transportation sector has brought up. The European Environment Agency report shows that transportation contributed by 15% of total $PM_{2.5}$ and 44 % of transportation emission come from passenger cars while 18% emitted by heavy-duty vehicles and buses (EEA, 2020). According to the International Transport Forum (ITF), transportation accounted for 30% of CO2 emissions in OECD countries and 16% of CO2 emissions in non-OECD countries (ITF, 2019). In addition to that, the energy consumed by the transportation sector increased by 19 Mtoe (IEA, 2018).

1.2 Electric Vehicles

Extending the concern on environmental protection and energy-saving, Electric Vehicles (EV) emerge as a potential technology in reducing environmental impacts associated with the transportation sector and helps in possible energy conservation.

Several studies in the past have shown that EVs can contribute significantly to the reduction of global warming potential (GWP) from 10% to 24% compared to diesel/gasoline vehicles. However, there are several elements that might affect the potential benefits of EV usage on the environment. Many studies have been conducted to show the effect of electricity generation mix and driving patterns of EVs on the environment. Samaras and Meisterling studied the GHG emissions of plug-in hybrid electric vehicles (PHEV) using different electricity generation mixes and patterns of driving in the US. Additionally, the source of electricity generation matters in reducing the environmental impact of EV. A study in the Texas power grid, whose electricity is generated using coal and natural gas, showed that the harmful emissions produced by EVs charged in these power grids were higher than the emissions produced while operating the conventional internal combustion engines (ICE).

Several European countries have started adopting EVs in different levels. According to (IEA 2018), countries in the Nordic region like Denmark, Finland, Iceland, Norway, and Sweden have shown significantly higher ratios of EV per capita, and the estimated value for the usage of EV by 2030 is about 4 million. In addition, there is an emerging trend in the US to use EVs in the expressways (Onat et al., 2015a, 2016c). Nevertheless, several studies have been conducted during the past to show different factors that affect the adoption process of EVs. The results reveal the existence of social, political, operational, financial, and technical barriers for the adoption of EV. The resistance that prevails when accepting any sort of innovation can also be seen in the case of EV adoption. Social networks contribute significantly to the adoption process. A study conducted in Amsterdam city reveals customer's choice in adopting EV over other alternative modes of transportation. The Netherlands is the only European country that has shown a progressive increase in the adoption of EV over time (Iea et al. 2014).

According to (Jaffe and Stains, 1994; Stoneman et al., 1994; Argote and Epple, 1990; Diamond, 2009) social factors such as lack of proper knowledge by potential adopters, low endurance of risk by consumers and the ability of EVs to fit in consumers' daily lives are some of the contributing factors that slow down the adoption process of EV. (Graham-Rowe et al., 2012; Peters and Dutschke, 2014; Hidrue et al. 2011) identified certain customer traits that could have a positive impact on the adoption of EV. Accessibility to charging infrastructures stay as a significant determinant for several customers to acknowledge the adoption of EV, thus creating tensions among users (Ghamami et al., 2014; Yeh, 2007; Struben and Sterman, 2008; Egbue and Long, 2012; Carley et al., 2013; Jensen et al., 2013; Krupa et al., 2014). The duration of charging the EVs and the driving range anxiety were also factors that escalated tensions among users (Egbue and Long, 2012). Government policies such as a decrease in the fuel prices and incentives for promoting a clean environment by opting eco-friendly modes of transportation can significantly influence the EV adoption process (Lane and Potter, 2007; Sovacool and Hirsh, 2009). The government of the Netherland has supported the adoption by banning oil-fueled cars (Oz, 2017). Still, economic issues such as fuel price influence the adoption of alternative fuel vehicles (Soltani-Sobh et al., 2017; Eppstein et al., 2011). The cost of EVs influences customer acceptance of EV (Rasouli and Timmermans, 2016; Jaffe and Stavins, 1994; Stoneman et al., 1994; Argote and Epple, 1990, Diamond, 2009). Thus, a need for proper sustainability assessment to evaluate the potential environmental savings of using EVs is felt necessary.

1.3 Electric Vehicles in the EU

Promoting sustainable urban mobility is a cornerstone for all EU member states. As a result, the EU countries promote the purchase and use of EVs in order to reduce their reliance on non-renewable resources such as gasoline and other fossil fuels. The support of EV in Europe was demonstrated through the deployment of charging infrastructures, conducting battery-related research, increasing customer awareness, and encouraging electricity utilization from renewable resources. For instance, in the Netherlands, there are nearly more than 32,000 charging slots spread across the state. Additionally, policies and incentives in EU member states were placed to encourage EV adoption. This can be seen in Germany and Austria, where the owners of EVs are relieved from paying taxes. Also, in France and Sweden, the car owner can exchange his diesel car for an EV, where he receives a sum total of up to €11, 000. For the above reasons, the adoption of EVs in EU countries is increasing over the years. In 2018, there were 1.2 million EVs on the roads of Europe, which is around 24% of the global fleet (IEA, 2019). Figure 1 shows these statistics in detail.

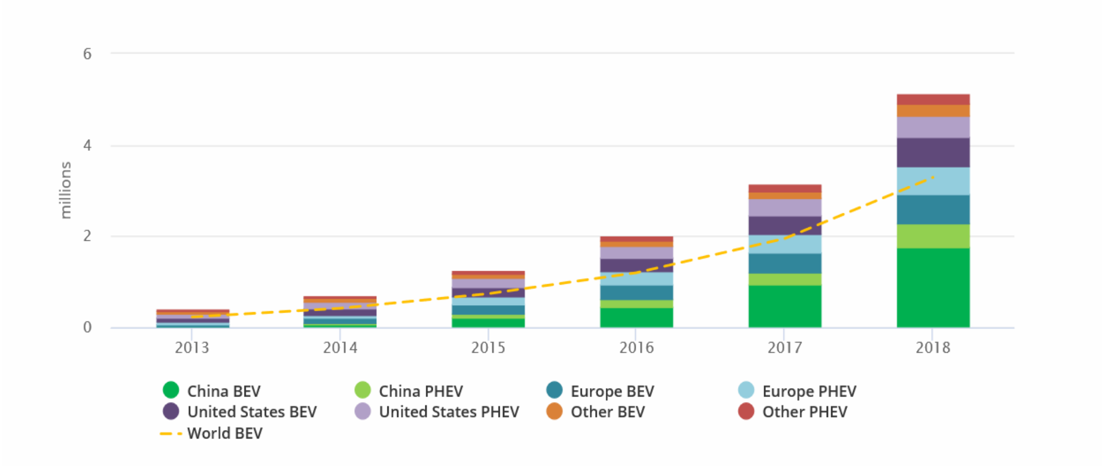


Figure 1. EV statistics for the years from 2013-2018 (source: global EV outlook, 2018).

1.4 Research Aims and Objectives

The main objective of this research is to are the following:

1. Analyzing and quantifying the impacts of EVs on water consumption, GHG emissions, and energy consumption.
2. Evaluating eco-efficiency of Electric Vehicles (EVs) across each EU member states in order to evaluate the sustainability performance in the operational phase of a BEV's life cycle. The eco-efficiency of each country was computed using three environmental indicators, namely water consumption, GHG emissions, and energy consumption, to represent the environmental impacts and one economic indicator, the GD per country.

1.5 Research Scope

In this study, the average electricity generation using energy mix was considered for EU countries, and a life cycle assessment (LCA) of BEVs have applied accordingly. This study focuses on the operational phase of BEV due to its enormous contribution to the energy, water and carbon footprints in contrast to other phases: the manufacturing and end-of-life (Onat et al., 2016b; Onat et al., 2014b). Accordingly, this study does not give due consideration to the impacts related to the manufacturing and end-of-life phases. The LCA used here considers per vehicle-miles traveled (VMT) as a functional unit. The impacts of the operational phase are divided into two stages: well to tank (WTT) and tank-to-wheel (TTW), and they are upstream and have direct effects on the energy usage in BEVs respectively. In the TTW stage, there is zero carbon emission and zero consumption of water. Despite this, both the stages WTT and TTW are consuming energy for different purposes. For WTT, the energy consumed is used for electricity generation while, for TTW, the consumption accounts for the vehicle's travel. The calculations of BEV's impact on the environment is expressed as:

$$F_{c,i} = FC \times (WTT_{c,t} + TTW_{c,t}) \quad (1)$$

where $F_{c,i}$ is the footprint for category impact c in each country i. FC stands for per mile consumption of fuel in kWh. The WTT and TTW are well to tank and tank to wheel operation, respectively, and they represent impacts of operation stages for category impact c in the country i. Figure. 2 illustrates the boundaries of the LCA analysis.

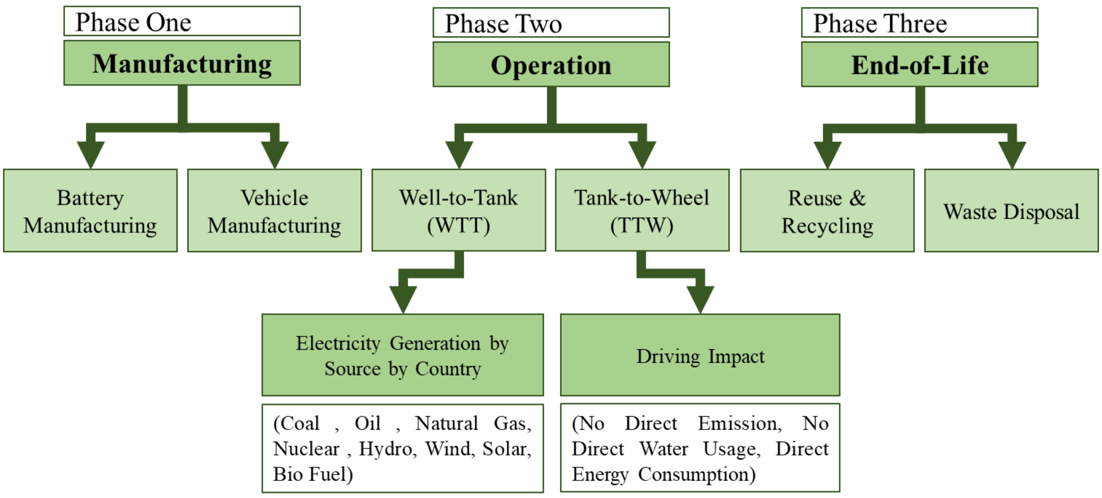


Figure 2. The scope and boundaries of life cycle assessment analysis.

1.6 Research Methodology

The research attempts to analyze the eco-efficiency of EVs in 28 EU member states using eight sequential steps, as shown in Figure 3. Initially, the four sustainability indicators were identified: three environmental and one economic. These indicators were selected to define better the sustainability performance of EV in EU countries. Then, the data of these selected indicators were collected and normalized to a common scale. The normalized data were then analyzed to identify any correlation among the indicators, after which different Principal Compound Analysis (PCA) weights were assigned accordingly. Then, the eco-efficiency of EV for each of the corresponding EU member states was calculated. Finally, the eco-efficiency results were modeled using ordinal regression, and subsequently, all required documentation was produced.

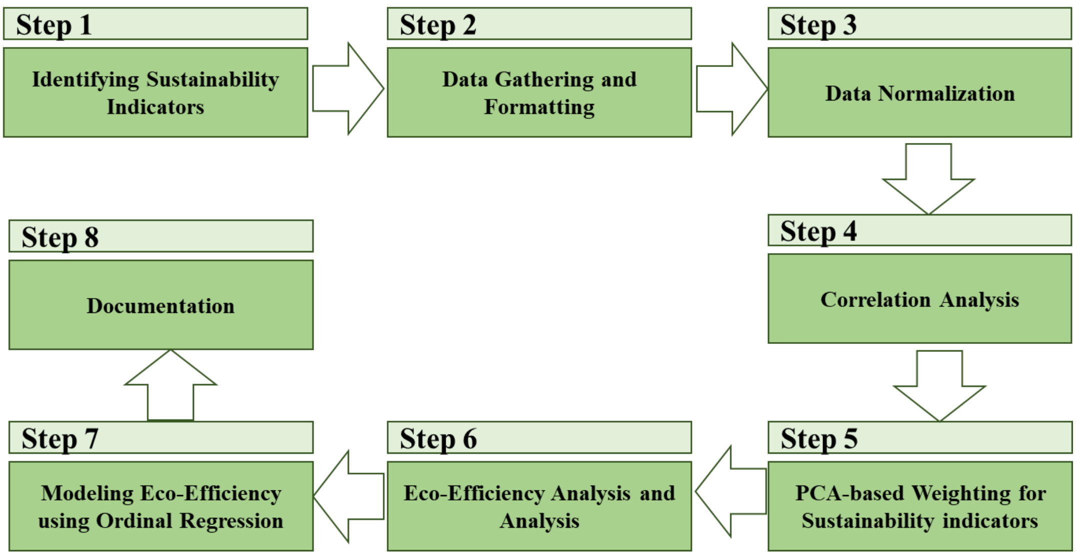


Figure 3. The methodology for the eco-efficiency assessment.

1.7 Research Questions

The research attempts to study the sustainability performances of EVs in 28 EU member states for electricity generation by different energy sources. The study uses eco-efficiency assessment measures combining both environmental impacts and economic benefits. The research thus attempts to address the following research questions namely;

1) How does each of the corresponding EU countries perform in terms of eco-efficiency of the EV using mix-sources of energy?

2) What are the potential environmental savings that can be achieved by EVs in each of the corresponding EU countries?

CHAPTER 2: LITERATURE REVIEW

This chapter is dedicated to highlighting the literature that studied electric vehicles. The following sections will report the sustainability assessment of electric vehicles, eco-efficiency assessment, and ordinal regression.

2.1 Sustainability Evaluation of Electric Vehicles

Previous research on EVs focused primarily on the environmental impacts associated with its usage. Thus, measures like CO_2 gas emissions, GWP and energy consumption behaviors were studied extensively and frequently used for assessments (Hawkins et al., 2012; Nordelöf et al., 2014; Onat, 2015a; Onat et al., 2015, 2018; Troy et al. 2012; Brinkman et al. 2005). The LCA introduced in 1991 studies and evaluated the sustainability of different products and systems by assessing the environmental impacts from the extraction phase to the end-of-life or recycling phase. Over the years, the LCA approach has gained publicity in the academic and industrial sectors due to its ability to customize components throughout the product life cycle in order to tackle different issues (Curran, 1996; Egilmez and Park, 2014). Reviews show that LCA is widely used for assessing environmental impacts (Egilmez et al., 2016) and for studying alternative vehicle technologies (Onat 2015a; 2015b; Onat et al. .2016b). (Samaras and Meisterling, 2008) employed LCA to evaluate the impacts of plugged-in hybrid electric vehicles (PHEVs) on the environment by measuring carbon emissions. In addition, (Faria 2012) applied LCA to assess the impacts of EVs versus gasoline vehicles on the economy and environment. (Onat et al., 2014) compared GHG emissions versus energy usage of different vehicles in the USA: conventional, HEVs, BEVs, and PHEVs using 19 indicators in three different charging scenarios. Studies by (Liu et al., 2014 in China; Ma et al., 2012 in the UK; Nanaki and Koroneos, 2013 in Greece; Yagcitekin et al., 2014 in Turkey) have also assessed the environmental impacts of conventional and alternative powertrain vehicles using LC approach. Studies conducted by (Onat et al., 2016) combined input-output LCA and multi-criteria optimization for calculating optimal vehicle distribution in the USA. In addition, (Ercan et al., 2016) developed a dynamic LCA to evaluate the possible reduction in GHG emissions when adopting public transportation. In literature, there were considerable improvements in terms of sustainability assessment, and the Life Cycle Sustainability Assessment (LCSA) approach was developed to overcome the limitation of LCA to assess new dimensions of sustainability, namely the economic and social aspects. This new framework embraces the standard LCA, life cycle costing (LCC), and Social LCA (SLCA) methodologies (Gloria et al., 2017). (Kloepffer, 2008) developed the LCSA framework with the help of (Finkbeiner et al., 2010).

2.2 Eco-Efficiency Assessment and Analysis

The concept of eco-efficiency has been used by (Egilmez et al., 2013/2014; (Tatari and Kucukvar, 2012; Iribarren et al., 2011) and by several numerous studies to analyze the life cycle inventory. Eco-efficiency is a widely used measure in the literature to assess sustainability since it takes into account economic dimensions versus environmental dimensions when assessing sustainability. Nevertheless, the computation of eco-efficiency becomes complex, especially when addressing several indicators with completely different measuring units. Linear programming is used to reduce such complexities. Techniques such as Principal Component Analysis (PCA) AND Data Envelopment Analysis (DEA) are some of the widely used techniques for such purpose. The DEA is applied to evaluate the impacts of several indicators on the environment, but this approach is not suitable if there is a correlation between these indicators. On the other hand, the PCA can assess the correlated sustainability indicators.

In literature, PCA is widely used to create composite indicators to make computation simpler. (Salvati and Carlucci, 2014) utilized the PCA technique to define a composite sustainability index by investigating 99 indicators. (Reisi et al., 2014) applied the PCA to create a composite sustainability index using nine indicators from the social, environmental, and economic dimensions of sustainability. (Bolcárová and Kološta, 2015) used PCA to rank 27 European countries by using an aggregated sustainability index with respect to the social, environmental, and economic dimensions of sustainability. (Mascarenhas et al., 2015) evaluated the sustainability performance of 10 Indian rural energy systems using the PCA technique. (Jiang et al., 2018) used PCA to create an aggregated sustainability assessment model combining social, environmental, and economic dimensions. Also, an analysis of eco-efficiency was conducted by the leading chemical company BASF, using the LCA for assessing the impacts of chemicals, processes, and products on the economy and environment(Lozano and Lozano, 2018; Saling et al., 2002). Moreover, the study conducted by (Park et al., 2015) utilized an economic input-output life-cycle assessment (EIO-LCA) and PCA technique for computing the eco-efficiency of 273 industries in the United States.

Recent studies have applied LCA combined with eco-efficiency to evaluate the eco-efficiency of the products, systems, or sectors. The combination of eco-efficiency concept with life cycle assessment framework (EEA-LCA) in this study showed significant improvements in assessing sustainability (Guinée, 2002; Rogers and Seager, 2009; Hellweg and Milài Canals, 2014; Egilmez and Park, 2014) and supports making eco-efficient decisions (Egilmez et al., 2016).

2.3 Ordinal Regression

Regression models are very popular in statistics. The application of regression methods in sustainability is a recent trend under the sustainability context (Kucukvar et al., 2019; Abdella et al., 2020). Several regression models have shown an excellent performance under different of industrial and service sectors, including manufacturing, healthcare, and transportation (AbdurRouf et al., 2018, Abdella, et al., 2016a, 2019a-b) The Ordinal regression analysis is used as a technique to study the relationship between explanatory and dependent variables with minimal assumptions (Dionysios et al., 2019). Ordinal regression finds applications in fields such as education, medicine, marketing, and tourism. (Keltgen, 2019; Ngozi, 2016; Drosos, 2015; Ombui, 2011; Chau-Kuang, 2004; Thomas, 2002) employed ordinal regression to analyze questionnaires. (Tosteson, 1994) applied ordinal regression to assess the liver function data for diagnostic tests. (Polyzos, 2011) also used ordinal regression to explore the current trends in the location of firms around the areas of touristic attraction in Greece. (Spais, 2006) examined the relationship of consumers in food-marketing using ordinal regression. In addition to that, an ordinal regression analysis was used to rank EU countries based on their sovereignty in work (Fernández-Navarro, 2013).

Recent studies have used ordinal regression to evaluate sustainable development. (Dionysios, et al., 2007; Dionysios et al., 2019) used ordinal regression to analyze the impacts of forest land usage on its resources in Greece. (Pérez-Ortiz, 2014) utilized ordinal regression to sort EU countries based on their progress towards sustainable development. However, no research has yet been done to study the eco-efficiency of EVs in EU states. In this paper, an ordinal regression model has been constructed for assessing the eco-efficiency scores of EU countries.

CHAPTER 3: ASSESSMENT METHODOLOGY

This chapter is dedicated to detail all the steps performed in this research work to assess and analyze the electric vehicles' eco-efficiency in the European United countries. The following sections will report and detail all the six steps of the proposed methodology (see Figure 3).

3.1 Step 1: Identifying Sustainability Indicators

Initially, three environmental indicators: GHG emissions, water consumption, energy consumption, and one economic indicator: Contribution to GDP were selected to evaluate the eco-efficiency of EVs. Table 1 shows the selected set of indicators for the assessment process.

Table 1. Main Categories of Sustainability Indicators

Main Categories	**Metrics**
Environmental Indicators	GHG Emissions (g CO2-eq /kWh) Water Consumption (L/kWh) Energy Consumption (kWh/kWh)
Economic Indicator	Contribution to GDP (US Dollar)

The GHG emissions, water consumption, and upstream energy consumption were calculated for assessing the EV impacts during the operational phase for EU countries that use electricity generated from mixed sources of energy.

3.2 Step 2: Data Gathering and Formatting

The data related to the production of electricity from the energy mix for EU countries were collected from the recent World Energy Statistics, Electricity Information, and Eurostat database. For studying the impacts associated with the EVs, EVs from the brand "Nissan" were considered. The vehicles were selected based on their kilo-watt hour energy consumption (30 kWh per 100 miles). The water consumption per source data was taken from the work done by (Onat et al., 2018). Table 2 shows the impacts of EVs on the selected set of environmental indicators used in the study.

Table 2. EV Impacts on Water Consumption, GHG Emissions, and Energy Consumption

No	Country Name	Water Consumption (L/kWh)	GHG Emissions (g CO2-eq /kWh)	Energy Consumption (KWh)
1	Austria	1.94	1.14	1.03
2	Belgium	1.08	1.22	1.36
3	Bulgaria	1.19	1.55	1.42
4	Croatia	1.74	1.34	1.15
5	Cyprus	1.03	1.76	2.00
6	Czech Republic	1.14	1.66	1.63
7	Denmark	1.04	1.43	1.59
8	Estonia	1.09	1.98	1.87
9	Finland	1.40	1.24	1.45
10	France	1.22	1.06	1.11
11	Germany	1.12	1.61	1.58
12	Greece	1.14	1.64	1.5
13	Hungary	1.08	1.36	1.46

No	Country Name		Water Consumption (L/kWh)	GHG Emissions (g CO2-eq /kWh)	Energy Consumption (KWh)
14	Ireland		1.07	1.62	1.54
15	Italy		1.22	1.49	1.49
16	Latvia		1.92	1.27	1.33
17	Lithuania		1.38	1.19	1.24
18	Luxembourg		2.00	1.07	1.01
19	Malta		1.00	1.35	1.31
20	Netherlands		1.04	1.74	1.72
21	Portugal		1.21	1.41	1.31
22	Poland		1.11	2.00	1.81
23	Romania		1.40	1.41	1.24
24	Slovakia		1.35	1.20	1.27
25	Slovenia		1.46	1.39	1.28
26	Spain		1.15	1.34	1.26
27	Sweden		1.66	1.00	1.00
28	UK		1.08	1.42	1.56

3.3 Step 3: Normalization of Data

The LCA results were structured into a matrix made up of 28 rows representing EU member states and four columns demonstrating three environmental and one economic indicator. The matrix structure held data with different measuring units and was used for conducting subsequent calculations. A transformation technique called "normalization" was applied in order to produce comparable and meaningful data. The data were normalized using the min-max technique (Eqn. 2) for values of a = one and b = 2 for an interval ranging from 1-2.

$$X_c{}' = a + \frac{(X_c - X_{\min})(b - a)}{X_{\max} - X_{\min}} \quad (2)$$

$X_c{}'$ stands for the normalized data of each country c and X_c is the raw data of each country c. The $X_{\min}$ and $X_{\max}$ represent the minimum and maximum value of data between all the countries. Table 3. compares the results of the three selected set of environmental indicators. The water consumption value holds the lowest average, while averages of energy consumption and GHG emissions were recorded to be high.

Table 3. Descriptive Statistics for the Selected Environmental Indicators

Variable	N	Min	Max	Mean ($\tilde{x}$)	SD (σ)
Water Consumption	28	1.000	2.000	1.294	0.297
GHG Emissions	28	1.000	2.000	1.425	0.258
Energy Consumption	28	1.000	2.000	1.411	0.255

3.4 Step 4: Correlation Analysis

The correlation/scatter analysis shows the behavior and the degree of correlation between the selected three environmental indicators (Figure 4).

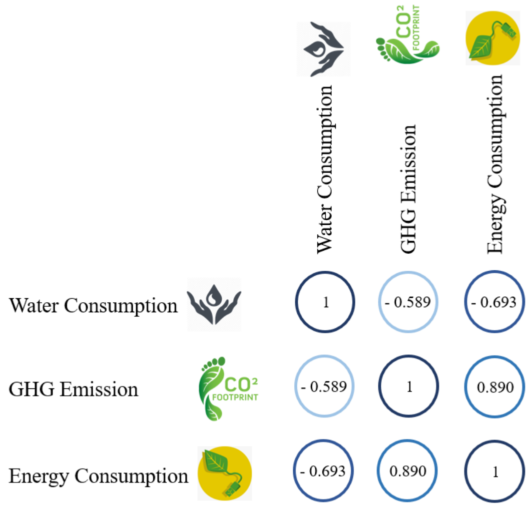


Figure 4. The Correlation matrix for EV impact on GHG emissions, water, and energy consumption.

It can be observed from Table 4 that the indicators, GHG emissions and water consumption are dependent on each other and negatively correlated with a value of -0.589. This translates the fact that, if the impact on water consumption increases, then the GHG emissions decreases. Similarly, if the water consumption value decreases, then the GHG emissions will increase. The indicators of energy and water consumption are highly dependent on each other and are negatively correlated with a value of -0.693. This means that if the impact on energy consumption increases, then the impact on water consumption decreases and vice versa. The degree of correlation between these two variables is more than the correlation value between GHG emissions and water consumption by a value of 0.104. Moreover, the behavior observed in energy consumption and water consumption relationships is more condensed compared to the GHG emissions and water consumption relationships, as shown in Figure 4. This means that GHG emissions hold a negligible impact on water consumption behavior when compared to the impact of energy consumption on water consumption. It can be noticed from the corresponding graph that GHG emissions and energy consumption depend on each other and hold a strong correlation with a correlation value of 0.890. This can be identified from the behavior of GHG emissions and the energy consumption exhibited in the graphs as they are clustered and move in the same direction (positive correlation) on the correlation line. This indicates the fact that if energy consumption increases, the GHG emissions increases, and vice versa.

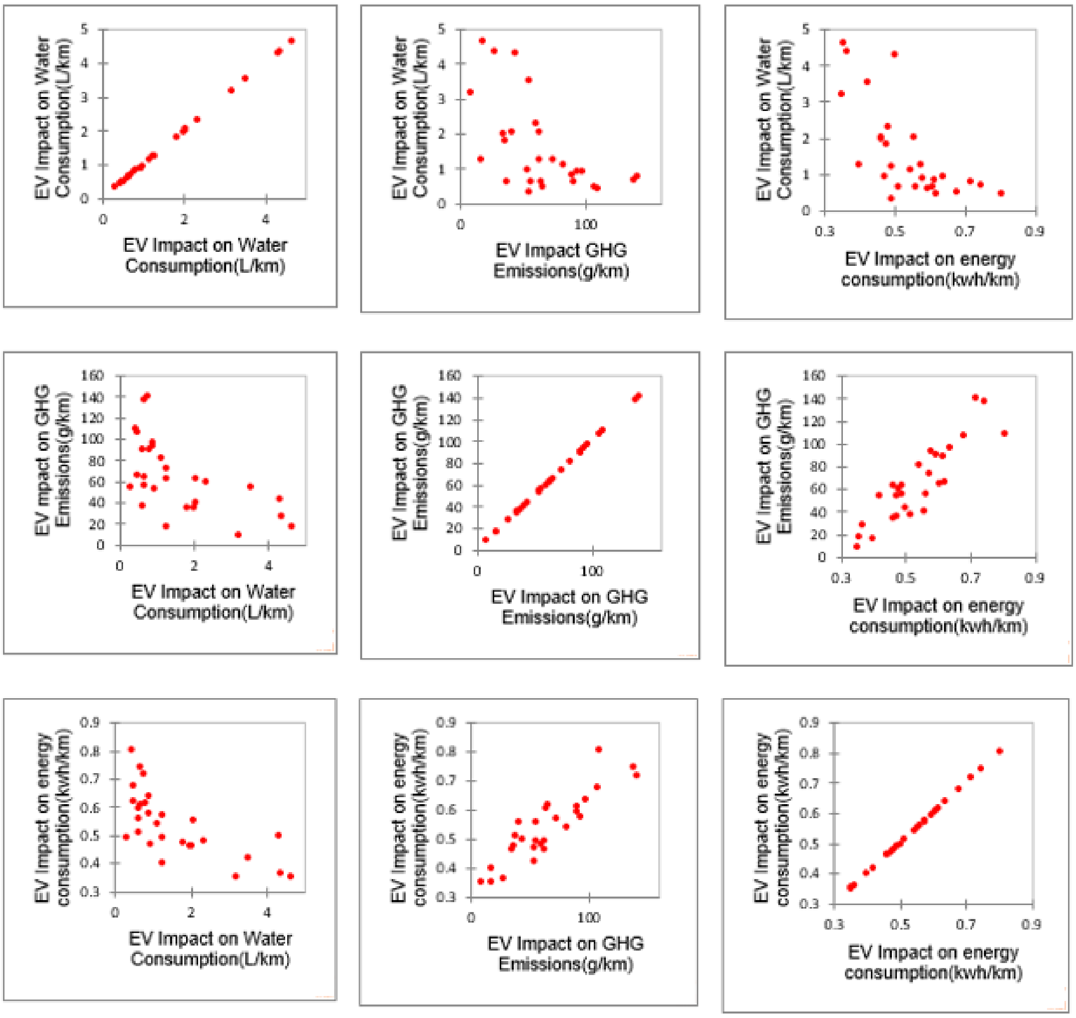


Figure 5. Correlation Graphs of EV Impact on GHG Emissions, water consumption, and energy consumption.

Figure 6. highlights the correlation relationship between the environmental indicators for analyzing the impacts of EV using a heat map image.

Country name	Water Consumption (L/km)	GHG Emissions (g/km)	Energy Consumption (Kwh/km)
Austria	1.94	1.14	1.03
Belgium	1.08	1.22	1.36
Bulgaria	1.19	1.55	1.42
Cyprus	1.03	1.76	2.00
Czech Republic	1.14	1.66	1.63
Denmark	1.04	1.43	1.59
Estonia	1.09	1.98	1.87
Finland	1.40	1.24	1.45
France	1.22	1.06	1.11
Germany	1.12	1.61	1.58
Greece	1.14	1.64	1.50
Hungary	1.08	1.36	1.46
Croatia	1.74	1.34	1.15
Ireland	1.07	1.62	1.54
Italy	1.22	1.49	1.49
Latvia	1.92	1.27	1.33
Lithuania	1.38	1.19	1.24
Luxembourg	2.00	1.07	1.01
Malta	1.00	1.35	1.31
Netherlands	1.04	1.74	1.72

Poland	1.11	2.00	1.81
Portugal	1.21	1.41	1.31
Romania	1.40	1.41	1.24
Slovakia	1.35	1.20	1.27
Slovenia	1.46	1.39	1.28
Spain	1.15	1.34	1.26
Sweden	1.66	1.00	1.00
United Kingdom	1.08	1.42	1.56

Figure 6. Heat map of normalized sustainability indicators data.

3.5 Step 5: PCA-based Weighting for Sustainability indicators

The PCA approach was used to combine the three environmental indicators to form a composite environmental value. Table 4 (a) shows the eigenvalues and the variance of PCA components as a percentage. The calculation of PCA value required components that have eigenvalues greater than or equal to 1. However, other remaining components were removed due to the lack of a significant impact on the outcomes of the study. Table 4 (b) shows the eigenvectors of three components that are used with the eigenvalues to compute the PCA value. The PCA value for each country was computed using Equation (3).

$$PCA\ value = C_1 Z_1 + C_2 Z_2 + C_3 Z_3 \tag{3}$$

Table 4. a) The Eigenvalues and Percentage of Variance (POV) of three components b) Eigenvectors of three components c) correlation of environmental indicators and the first component

PCA-based analysis			F1	F2	F3
	a)	Eigen Value	2.455	0.447	0.098
		Variability (%)	81.849	14.886	3.265
		Cumulative (%)	81.849	96.735	100.000
	b)	Water Consumption	-0.529	0.833	0.163
		GHG Emissions	0.588	0.498	-0.637
		Energy Consumption	0.612	0.241	0.753
	c)	Water Consumption	-0.829	0.556	0.051
		GHG Emissions	0.922	0.333	-0.199
		Energy Consumption	0.958	0.161	0.236

The correlation of environmental indicators and the first component is shown in Table 4 (c). There occurs a strong positive correlation between GHG emissions, energy consumption values, and the PCA value. This means that, when increasing the value of GHG emissions or energy consumption, the value of PCA also increases. On the other hand, it can be noticed that the negative correlation between water consumption value and the PCA value is strong. This translates the fact that, when increasing the value of water consumption, the value of PCA decreases.

The variables factor map (Figure 7) displays the vector representation of the three environmental indicators. It displays the POV of the first and second components in PCA. The GHG emissions and energy consumption holds a negative correlation with water consumption and is represented by their opposite directions.

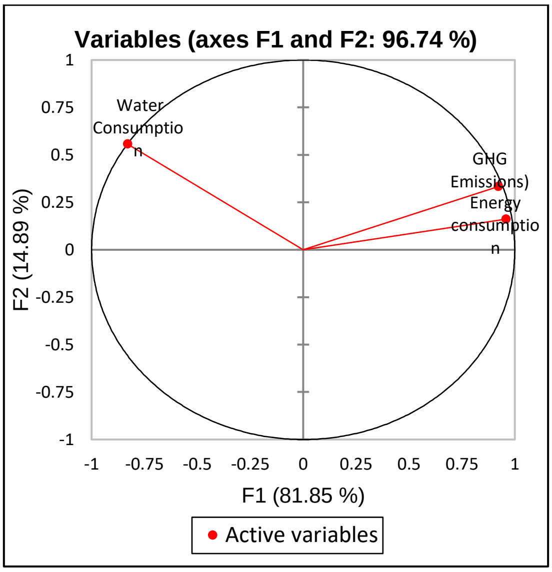


Figure 7. The variables factor map (PCA).

In this paper, the first component was used to calculate the Composite Environmental Index (CEI) value since it has an eigenvalue that is greater than one by using Equation (4):

$$CEI = -0.529I_1 + 0.588I_2 + 0.612I_3 \tag{4}$$

Where I_i is a corresponding environmental indicator, as shown in Table 4(b).

3.6 Step 6: Eco-Efficiency Calculations and Analysis

The eco-efficiency method combines both environmental and economic dimensions for better assessment of the sustainability of EVs. Raw eco-efficiency scores were calculated as the ratio of the country's contribution to GDP (by considering electricity prices) over the composite environmental index (CEI) as presented in Equation (5). The normalized eco-efficiency scores of EU countries ranged from an interval value of zero to one (Table 5). France has the highest eco-efficiency score since it holds a minimum value for the environmental composite index. While Malta has the lowest eco-efficiency score with a high CEI value. Countries with lower CEI values hold higher eco-efficiency.

$$\text{Eco-efficiency}=\frac{\text{Country's Contribution to GDP}}{\text{Composite Environmental Index (CEI)}} \tag{5}$$

However, a min-max technique, as applied by Park et al. (2015), is required to re-scale the raw eco-efficiency values so they can be compared between the countries, as governed by the Equation (6).

$$EF_c' = \frac{EF_c - EF_{\min}}{EF_{\max} - EF_{\min}} \tag{6}$$

EF_c stands for the raw eco-efficiency score for each country c. The $EF_{\min}$ and $EF_{\max}$ represent the minimum and maximum scores of eco-efficiency between all the countries. Table 5 presents the eco-efficiency scores that were obtained by dividing the electricity prices of EU countries with CEI values. The scores were normalized using the min-max technique (Eqn. 2) with a = 0 and b = 1 to put values in zero to one interval.

Table 5. Composite Environmental Index and Normalized Eco-Efficiency Scores for EU Countries

No	Country Name		Contribution to GDP (Electricity Price in USD)	Composite Environmental Index(CEI)	Normalized Eco-Efficiency Score
1	Austria		0.22	2.74	0.72
2	Belgium		0.32	3.17	1.00
3	Bulgaria		0.11	3.65	0.01
4	Croatia		0.15	3.12	0.32
5	Cyprus		0.24	4.59	0.16
6	Czech Republic		0.16	4.03	0.82

No	Country Name	Contribution to GDP (Electricity Price in USD)	Composite Environmental Index(CEI)	Normalized Eco-Efficiency Score
7	Denmark	0.33	3.70	0.00
8	Estonia	0.14	4.69	0.36
9	Finland	0.18	3.33	0.57
10	France	0.19	2.69	0.82
11	Germany	0.34	3.91	0.32
12	Greece	0.20	3.84	0.11
13	Hungary	0.13	3.46	0.26
14	Ireland	0.24	3.86	0.46
15	Italy	0.28	3.66	0.65
16	Latvia	0.18	3.25	0.38
17	Lithuania	0.12	3.02	0.15
18	Luxembourg	0.17	2.63	0.51
19	Malta	0.14	3.26	0.19
20	Netherlands	0.17	4.23	0.16
21	Portugal	0.25	3.35	0.09
22	Poland	0.16	4.65	0.65
23	Romania	0.15	3.28	0.23
24	Slovakia	0.16	3.07	0.35
25	Slovenia	0.18	3.31	0.35
26	Spain	0.29	3.21	0.87
27	Sweden	0.18	2.52	0.58
28	UK	0.20	3.66	0.37

3.7 Step 7: Modeling Eco-Efficiency using Ordinal Regression

Table 6 below shows coefficients, standard errors, Wald test, and associated p-values (Sig.) and 95% confidence interval of the coefficients.

Table 6. Parameter Estimates of Three Environmental Indicators

		Est.	Std. Error	Wald Test	df	Sig	95% Conf. Interval Lower Bound
Threshold	[V6 = High]	3.387	4.975	.463	1	.496	-6.365
	[V6 = Low]	4.569	5.003	.834	1	.361	-5.237
Location	V3=Water Consumption	2.861	2.059	1.932	1	.165	-1.174
	V4=GHG Emissions	-1.665	3.194	.272	1	.602	-7.925
	V5 = Energy Consumption	2.345	3.710	.399	1	.527	-4.927

Results from Table 6 show that both the water and energy consumption values are statistically significant, while the GHG emission values are not significant. A unit increase in the water consumption value can result in an increase of around 2.861 in terms of eco-efficiency, given all the other environmental indicators are constant. In addition, a unit increase in the energy consumption value can result in an increased eco-efficiency value of more than 2.345, provided all the other environmental indicators are constant. The threshold values are shown in Table 6. They indicate where latent variables are cut to make three groups of eco-efficiency scores.

3.8 Step 8: Documentation

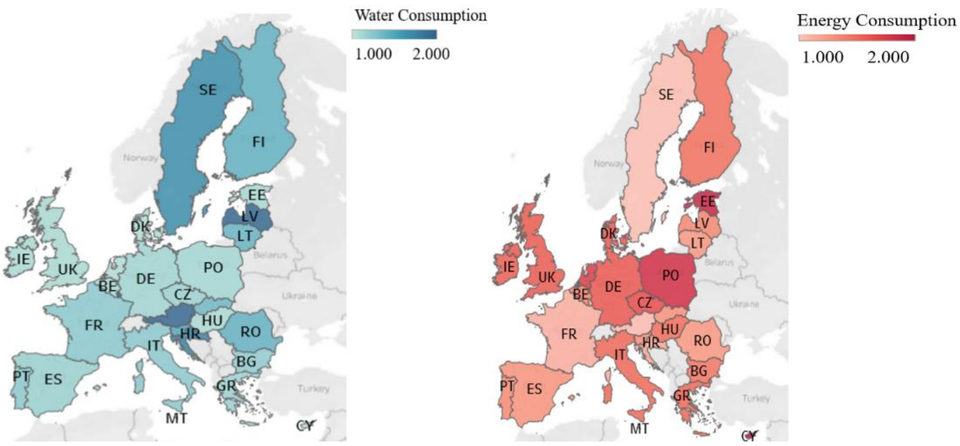
The documentation process involves collecting, processing, and analyzing data that includes electricity prices, water consumption, GHG emissions, and energy consumption for electricity generation. Also, it includes the calculation of the impacts of EVs on the environmental and economic dimensions of sustainability. In addition, it includes the calculation of eco-efficiency results and the building of statistical models. Well-designed documentation translates information that can be easily accessed, monitored, communicated, and shared.

CHAPTER 4: ECO-EFFICIECY ANALYSIS AND COMPARISON

This chapter is dedicated to compare and group eco-efficiency of the electric vehicle in the European United countries.

4.1 Eco-Efficiency Performance Comparison

The impact of EVs on water consumption varies among EU countries, as shown in Figure 8a. EVs in countries like Luxembourg, Austria, and Latvia hold a higher water consumption value than countries like Cyprus and Malta, whose water consumption values are comparatively low (Figure 8a).



a) b)

Figure 8. a) Impact of EVs on water consumption (L/kWh) in EU map b) Impact of EVs on the energy consumption (kWh/kWh) in EU map.

The data for upstream energy consumption per source of energy was derived from the eGRID database. The impact of EVs on energy consumption was 5% for Estonia and Cyprus (Figure 8b, Figure 9). While, for countries like Bulgaria, the Czech Republic, Denmark, Finland, Germany, Greece, Hungary, Ireland, Italy, and the Netherlands, the percentage value amounted to 4%. Also, Belgium, France, Croatia, Latvia, Lithuania, and Malta held an impact of 3% on energy consumption. The impact of Austria and Luxembourg was 2%. The rest of the EU member states held an impact of 27% on energy consumption. Countries like Cyprus, Estonia, and Poland consumed higher shares of energy, while countries like Sweden, Luxembourg, and Austria had lower consumption values.

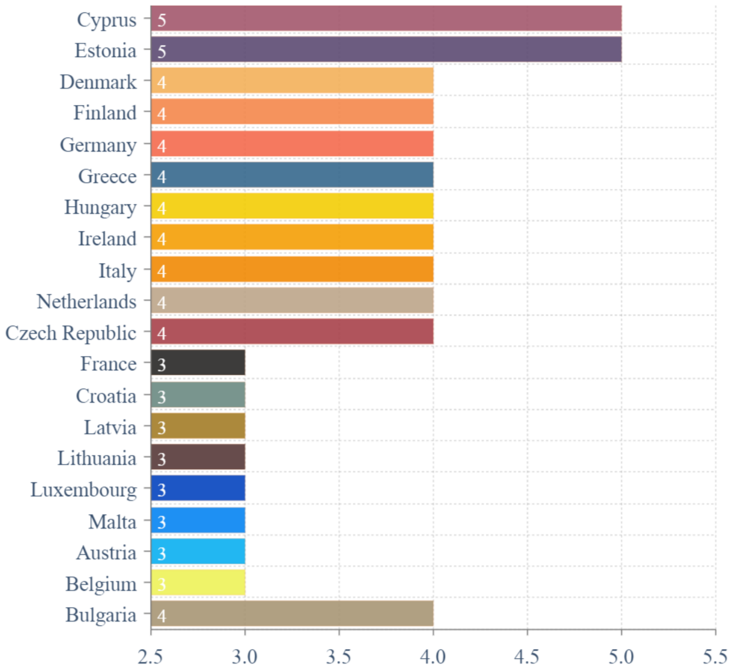
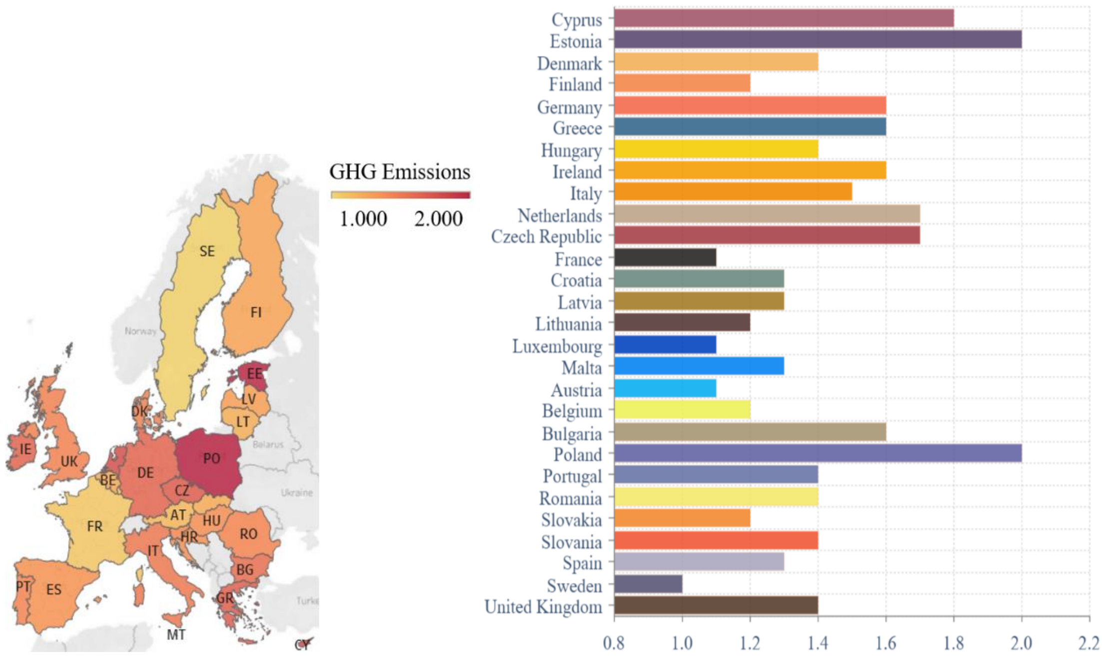


Figure 9. Impact of electric vehicles on energy consumption.

The GHG emissions data were retrieved from the UK parliamentary Office of Science and Technology. Figure 10 represents that EV impact on GHG emission was highest in Poland, Estonia, and Cyprus and was lowest in Sweden and France due to their cleaner energy sources.



a) b)

Figure 10. a) Impact of EVs on GHG Emissions (gCO2-eq/kWh) in EU map b) Impact of EVs on GHG Emissions.

Moving on to interpreting and comparing the eco-efficiency performance, the eco-efficiency scores hold a direct relationship with the "contribution to GDP" value and a converse relation with the CEI. As shown in Figure 11, Belgium can be tagged as the highest eco-efficient EU member state due to its low value of CEI and high value on "contribution to GDP." Spain is the second highest eco-efficient EU member state since it has a lower value of CEI and holds a greater value for the index "contribution to the GDP." The interpretation follows ranking "Denmark" as the third highest eco-efficient EU member state since it holds a larger value for CEI and the index "contribution to GDP." Although Germany has the maximum value for contribution to GDP, the large enough value of CEI makes it the fourth highest eco-efficient EU member state. Sweden has the minimum CEI value among all the EU countries; hence it is less eco-efficient when compared with Belgium, Spain, Denmark, and Germany due to its low value for the index "contribution to GDP." On the other hand, Estonia is the least eco-efficient EU country since it holds the highest value for all three environmental indicators and, accordingly, the largest value of CEI.

The results in this paper have to be seen in the light of some limitations related to collected data. The primary limitation is limited access to recent data, especially data related to impacts of electric vehicles on water consumption, GHG emissions, and energy consumption in European Union countries. Accordingly, it might affect calculations and get up-to-date scores of eco-efficiencies in the EU.

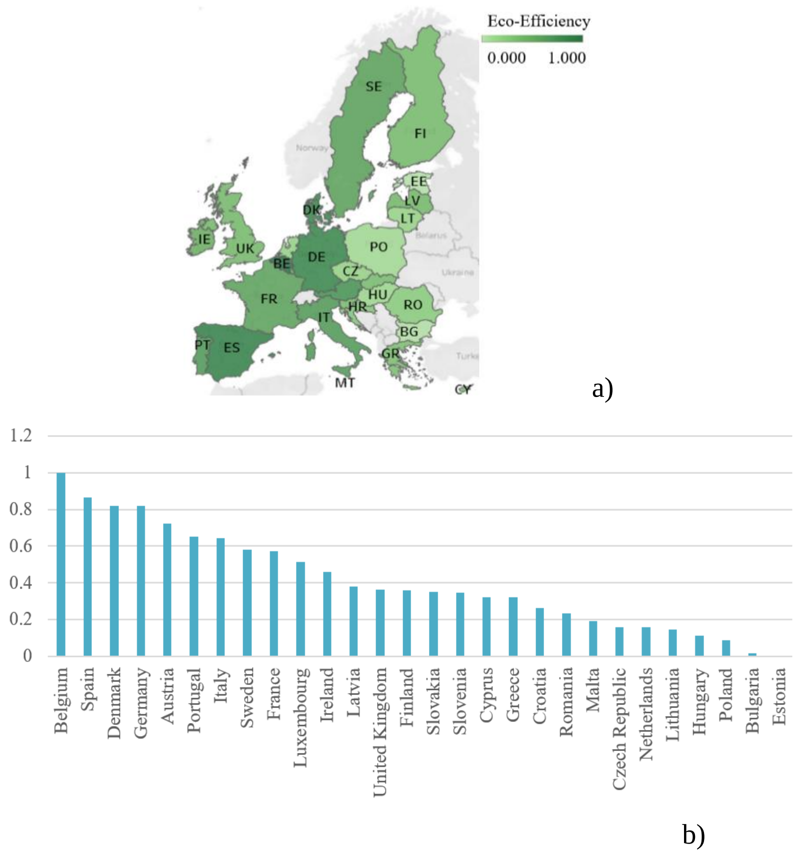


Figure 11. a) Eco-efficiency scores for EU member states on European map b) Eco-efficiency ranking of EU member states in descending order.

4.2 Eco-Efficiency Performance Grouping

Further, to categorize EU countries based on their performance, countries have been split into three groups (High, Medium, and Low) based on their eco-efficiency scores. Using a box plot (Figure 12), EU countries with eco-efficiency scores ranging from 0 to 0.176 fall under the Low eco-efficiency group. The EU countries that fall in medium eco-efficiency group have eco-efficiency scores ranging from 0.176 to 0.613. Finally, the EU member states with eco-efficiency scores from 0.613 till one falls under the High eco-efficiency group.

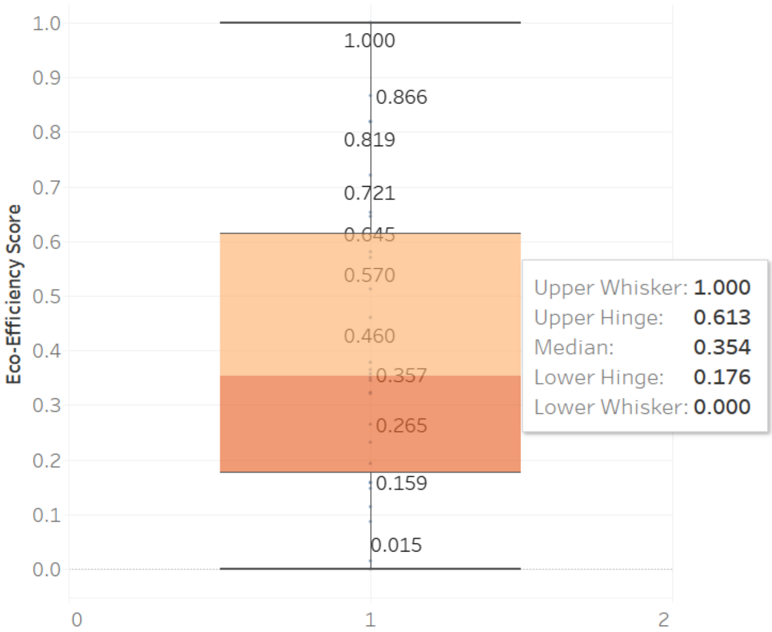


Figure 12. Box plot of eco-efficiency scores.

Figure 13 categorizes member states based on their eco-efficiency performance level, and Table 7 represents a list of EU countries in three groups based on High, Medium, and Low-performance level.

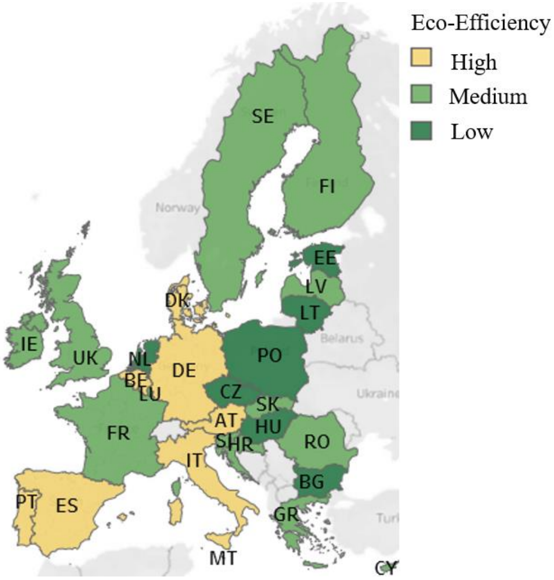


Figure 13. Eco-efficiency groups in the EU map.

Table 7. Eco-efficiency performance categorization of EU member states

High Eco-Efficiency	Medium Eco-Efficiency	Low Eco-Efficiency
Austria	Cyprus	Bulgaria
Belgium	Finland	Czech Republic
Denmark	France	Estonia
Germany	Greece	Hungary
Italy	Croatia	Lithuania
Portugal	Ireland	Netherlands
Spain	Latvia	Poland
	Luxembourg	
	Malta	
	Romania	
	Slovakia	
	Slovenia	
	Sweden	
	United Kingdom	

CHAPTER 5: CONCLUSION, AND FUTURE WORK

This chapter is dedicated to report results and recommendations and to show possible future work.

5.1 Conclusions and remarks

In this paper, the eco-efficiency of EVs using a country's energy mix in 28 EU member states were studied. The study focused on three environmental (GHG emission, water consumption, and energy consumption) indicators and one economic indicator (contribution to GDP) in order to measure the sustainable performance of EVs. A methodology combining LCA and PCA was developed and applied to compute the eco-efficiency of EU countries. Results showed that Belgium is the most eco-efficient while Estonia is the least eco-efficient. In addition, the highest percentage of electricity generation in countries who fall in the high-efficiency group comes from natural gas, nuclear, hydro and wind. Furthermore, the highest percentage of electricity generation in countries that fall in the low-efficiency group comes from oil and coal, and those countries can improve their eco-efficiency. They increase their reliance on clean sources by 20%. Moreover, the countries that fall in medium-efficiency groups have quite a balance of different mix of sources, and those countries can improve their eco-efficiency. They increase their reliance on clean sources by 2%. The findings can help in developing sustainable transportation policies and provide guidance to make informative decisions accordingly.

5.2 Recommendations and Future Work

The study can further be extended to assess the eco-efficiency globally and benchmark the eco-efficiency level. Also, future works can include more sustainability indicators from the social, environmental, and economic dimensions of sustainability. Thus, it can help policymakers to benchmark the environmental impacts and accordingly support achieving 2030 United Nation's Sustainable Development Goals. For future research works, Methods such as variable selection, including stepwise regression, ridge, and LASSO regression can be used to identify the most significant indicators to be included in the process of developing eco-efficiency indicators; see Jiang et al., (2012), Abdella et al., (2014, 2016b, 2017, 2019c), Kim, et al., (2019), and Abdella et al., (2020).

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